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Who Loses Out? Registration Order, Course Availability, and Student Behaviors in Community College

In California, the combination of budget cuts and high unemployment from the Great Recession has resulted in "overcrowded" conditions, with more students attempting to enroll in fewer available classes. State-level policy recommendations have focused on altering registration priorities to mitigate the impact of overcrowding, but it is unclear whether these changes will impact enrollment, as little is known about student behavior within these systems. Present-biased individuals who must engage in immediate efforts to obtain delayed rewards may procrastinate before beginning a task and vary in how intensely they engage in a task once they begin, and registration is found to be no exception. Varying levels of delay and intensity were found to be predictive of students' course-taking patterns, even after controlling for a wide range of background characteristics, including previous registration delay and intensity. As a result, many courses that met graduation or transfer requirements had seat availability during the registration process and only closed near the beginning of the semester, which is in contrast to common narratives of overcrowding. Student registration is an understudied part of the college process, but suboptimal registration behaviors are shown to have significant consequences on the likelihood of college enrollment and retention.

Keywords: community college, overcrowding, registration, procrastination

Introduction

Undergraduate enrollment in U.S. postsecondary institutions has steadily climbed since the 1970s, but postsecondary completion rates have stagnated or declined, with students increasingly taking six or more years to earn their degree (Aud et al., 2012; Turner, 2004).

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Research has continued to identify and remedy barriers to postsecondary enrollment and retention, but simply retaining students will not increase completion rates unless the infrastructure is in place to serve them. The Great Recession led to extreme cuts in support for higher education, with 48 states spending less money in 2013 than 2008 (Oliff, Palacios, Johnson, & Leachman, 2013). In California, general fund support for higher education has been reduced by billions of dollars, dramatically increasing the cost of tuition and fees for students at most of the state's higher education institutions (Baum & Ma, 2012; Taylor, 2012). Four-year institutions have been forced to reduce course offerings and to restrict access to new and transfer students, which has pushed more students into the community college system (Varlotta, 2010)

The combination of decreased resources, fewer course offerings, and increased enrollments has resulted in what some describe as impacted or "overcrowded" conditions in the community college system. Although there is no consensus of what constitutes overcrowding, one definition of impaction is "student demand that exceeds the financial and/or physical capacity of the institution" (Bahr, Gross, Slay, & Christensen, 2014). As community colleges are more likely than other institutions to respond elastically to increased demand (Bound & Turner, 2007), this implies that the public provision of higher education has been exhausted. In practice, impaction is usually described as a combination of increased class size and lengthy wait-lists (Bohn, Reyes, & Johnson, 2013; Gardner, 2012), which prevent students from the opportunity to enroll in the courses needed for degree completion. A recent survey by the Pearson Foundation found that California's community college students were almost twice as likely to report being unable to enroll in courses than the national average (Pearson Foundation, 2011).

With news stories and policy reports focusing on the plight of students wait-listed or closed out of the system, California, along with a number of other states, has increasingly focused on altering registration priorities as one potential solution to impaction (Bahr et al., 2014). California's community colleges utilize a wide range of enrollment practices, but consistently assign earlier registration appointments to students with higher unit totals or who have been registered longer within the college (Bahr et al., 2014). This has led two separate state commissions to declare that California "is rationing access to community colleges, but not in a rational way" (Little Hoover Commission, 2012, p. V) resulting in "policies that enable students to wander around the curriculum, . . . and accumulate an unlimited number of units . . . [which is] a disservice to enrolled students and to those who cannot get into the system due to a lack of available classes." (California Commu-

nity Colleges Student Success Task Force, 2012, p. 33). This has led to the proposal of a number of policies, such as giving earlier registration priority to students who fully matriculate by completing assessment, orientation, and counseling services prior to registration (Taylor, 2011). State Bill 1456, approved in September 2012, tackles the issue from the other end, as continuing students with lower academic performance or high unit counts who have not yet earned a degree will lose registration priority and be placed at the end of the line.

This study attempted to explicitly map out the relationship between assigned registration times and course availability, in order to provide a more nuanced understanding of how impaction affects students in a representative community college. I found that many courses that met graduation or transfer requirements had seat availability during the registration process and only closed near the beginning of the semester, which is in contrast to common narratives of impaction. I explain this phenomenon through the introduction of two individual-level registration behaviors—search delay and intensity—that are shown to be as important as the institutionally-assigned registration time in determining course-taking patterns. My findings imply that students facing closed courses or long wait-lists may be those with low commitment to pursuing their college education, have a weaker understanding of how to navigate the registration or community college system, or who are simply prone to procrastinate; each of these possibilities are discussed in turn. I also show that lower retention rates for students with late registration a common finding in previous research—were drastically smaller or insignificant after taking into account the number of units attempted. In other words, the mechanism that predicts whether late registrants persist is whether they were able to eventually enroll in a meaningful number of courses, and I describe how this might occur through persistent efforts both inside and outside the registration process. Taken together, these findings build upon our limited knowledge of college registration to develop a stronger framework for modeling student behavior and constructing appropriate policy solutions to issues of impaction. Student registration is an understudied part of the college process, and suboptimal registration behaviors, at least in overcrowded conditions, may have serious consequences on the likelihood of college enrollment and retention.

Literature Review

State, national, and global policy reports frequently cite the need to produce more college-educated workers, and overcrowded colleges could exacerbate this problem. Although few studies focus on the role of supply-side capacity in higher education, recent work suggests that a reliance on government and private funding prevents colleges and universities from raising tuition and fees sufficiently to respond elastically to increased demand (Bound & Turner, 2007). Colleges that are unable to accommodate demand may choose to restrict enrollment or reduce resources per student, which may cause university quality to decrease and may lower students' completion rates (Bound, Lovenheim, & Turner, 2010; Bound & Turner, 2007; Kane & Orszag, 2003). One mechanism by which time to degree may increase or degree attainment may decline is through "course scarcity," or the inability to enroll in the courses necessary for completion (Kurlaender, Jackson, Howell, & Grodsky, 2012). These supply-side changes can be seen in California's community college system, where both resources per full-time equivalent student and the total number of course sections offered has declined over 20% from 2006-07 to 2011-12, even though fees have risen from \$26 to \$46 per unit over the same time period (Bohn et al., 2013). However, not all of the available evidence suggests that declining resources, at least historically, are a significant problem in the community college setting. Bound, Lovenheim, and Turner (2010), examining declining postsecondary completion rates at community colleges, found that "conventionally measured academic resources . . . explain little of the completion rate decline, while declines in college preparation account for almost 90% of the total drop in completion rates" (p. 131). Evidence on the relationship between institutional resources and completion rates is mixed (Goldrick-Rab, 2010), with recent work on community colleges finding no effect of resources on educational attainment (Stange, 2012). Course completion and success rates in California actually improved during the crisis, though obviously this pertains to only those students who were successfully able to enroll in courses (Bohn et al., 2013).

It is unclear whether California's proposals to alter registration priority will shift course availability, as there are only a handful of studies that have explicitly focused on students' actual behaviors during the registration process. A small number of studies compared early and late registrants at both community colleges and universities, with late registrants typically defined as those who enrolled in a course after the semester began. These studies consistently found that students who registered later exhibited lower course completion and retention rates (Ford, Stahl, Walker, & Ford, 2008; Hale & Bray, 2011; Safer, 2009; Smith, Street, & Olivarez, 2002). Interviews with a handful of late registrants identified a desire to register on time that was confounded by circumstances and bad luck (Bryant, 1996), but "bad luck" by itself should not help explain why these students would then be less likely to return the following semester to complete their degree. Hagedorn, Maxwell,

Cypers, Moon, and Lester (2007) analyzed a more complex set of enrollment decisions, finding lower course completion rates for students with excessive add and drop behaviors in the first four weeks of the semester. Unfortunately, these studies are limited in the guidance they can provide about registration and impaction more generally. First, each focused on registration after the semester began, but none discussed the substantial heterogeneity in behaviors that occur during the initial stages of the registration process. Second, each study examined GPA or retention as their primary outcome, but none examined the intermediary step of what types of courses students took. Late registration may result in student taking no courses, as might be the case in impacted colleges, but these students appear to be excluded from the analyses. Finally, no study differentiated between assigned (as opposed to observed) registration times, even though community colleges assign students sequential registration priority based on a number of characteristics that are likely to be related to their desired course-taking patterns and academic goals (Bahr et al., 2014). This article resolves these issues by identifying the distinct registration groups, restricting comparisons to students within the same assigned registration time, and focusing on the relationship between registration behaviors and course-taking, inclusive of students who drop out of the college without taking a single class.

A recent paper by Kurlaender et al. (2012) did not focus explicitly on students' registration patterns, but provided the only study to date that tests whether late registration might have a causal impact on degree attainment or time to degree. Leveraging randomized registration times for students attending the University of California, Davis, they found that equivalent students with later registration times were more likely to attempt to register in a course and be locked out, but they found no negative long-term impact for students with consistently "bad luck," meaning those who consistently received later registration times than their peers. Although Kurlaender et al. (2012) provides convincing evidence that late registration had limited impact, this study occurred in a moderately selective four-year institution where admissions decisions prior to registration may have been designed to take into account institutional supply. As such, their study might not generalize to open-access institutions, such as community colleges.

Conceptual Framework

Models of college student behavior typically rely on a human capital framework, wherein individuals make decisions after weighing their relative costs and benefits on present and future outcomes (Becker, 1964; Tinto, 1975). For example, Hagedorn et al. (2007) assumed rational

choice theory to understand course selection, implying that haphazard add and drop behaviors were a result of decisions intended to optimize individual benefit. In the rational actor framework, late registration likely reflects a relatively weaker commitment to earning a college education, thus explaining why it is correlated with lower retention rates.

There are a number of reasons for assuming the rational actor model may be flawed in this context. First, students with similar cost-benefit perspectives might vary in their understanding of the registration process, causing those with weaker knowledge to register later. This belief is supported by research that has documented the challenges in the transition from high school to college, particularly for ethnic minority and first-generation college-going students (Goldrick-Rab, 2010; Rosenbaum, Deil-Amin, & Person, 2006). As weak links between high schools and broad-access institutions leave many students unaware of the requirements needed to enter a community college, traditionally underrepresented students may have less ability to access this information in time to transition smoothly (Venezia, Kirst, & Antonio, 2003).

An alternative hypothesis draws from the economic and psychology literature, which has long noted the tendency of individuals to be "present-biased" and discount future benefits, leading them to delay tasks with short-run costs and long-run rewards (Ainslie, 1975; Schouwenburg, 1995). This is an apt description for student registration; in the college studied, students were given the opportunity to register from two weeks to almost two months before courses begin. Procrastination affects all individuals, but has been found to be higher among younger and less educated individuals (Bettinger & Slonim, 2007; Steel, 2007), descriptions clearly applicable to community college students. Although some theories suggest that procrastination is linked to an individual's level of present bias, competing explanations suggest that procrastination may be a function of task avoidance associated with anxiety or negative self-esteem, poor self-regulation, and self-efficacy (i.e., the belief in one's ability to complete a task) (Steel, 2007), choice overload (Iyengar & Lepper, 2000), or excess optimism (O'Donoghue & Rabin, 2001). All of these factors may be relevant in the community college context: students may delay registration in math courses over performance anxiety, might be overwhelmed by the number of choices available, or anticipate that they can overcome procrastination through additional effort later. Nonetheless, these varied hypotheses suggest that student behaviors should not be analyzed in a purely rational actor framework.

In this study, I draw guidance from work on procrastination to study the relationship between student behaviors and academic outcomes. Similar to previous research on impatience and job search among the unemployed (DellaVigna & Paserman, 2005; Paserman, 2008), I examine how long individuals delay before they begin to look for courses, and how intensely they search once they begin. Although my data do not allow me to disentangle the extent to which variation in registration delay and intensity are driven by each of these competing theories listed above, my results provide suggestive evidence that students engage in behaviors that are not driven purely by lower levels of college commitment or information barriers. Specifically, I found that a student's registration behaviors tended to be consistent across semesters, even though these students had made significant progress toward graduation and had ample familiarity with the registration process. These results support the idea of utilizing a present-bias framework when studying registration, in order to construct appropriate government or institutional-level policy responses to improve registration behaviors.

Data and Methods

Data for this project came from one large California community college and included students' transcripts, demographic characteristics, assigned registration times, and a detailed history of every registration attempt. This article focused on students in the fall semester of the 2011–12 academic year. Assigned registration times began approximately eight weeks before the semester started for the longest-enrolled continuing students and two and a half weeks before the semester started for new students. Any student registered in the previous semester was automatically assigned a registration time whether they intended to enroll or not, so I restricted all analyses to students who attempted to register in at least one credit-bearing course.

For simplicity, I focused my analysis on three registration groups.¹ The first group was all "Continuing" students, defined as students who had initially enrolled at least one year prior to the Fall 2011–12 semester. The second group consisted of all "Second Semester" students who entered the prior spring, as these students received registration appointments after all other continuing students. The final group was "New" students, who received the last assigned registration times. Although the college divided new students into two separate groups—matriculated and nonmatriculated—I focused the majority of the analysis on nonmatriculated students, who comprised more than two-thirds of all incoming students, due to potential errors in the registration behavior of some matriculated students.² Except where noted, all references to new students should be interpreted as nonmatriculated only. Matriculated students

were those who completed all three matriculation steps at least four weeks prior to the beginning of the semester: taking a placement exam. attending an orientation (a 30 minute online version was available), and meeting with a counselor. Nonmatriculated students had not completed these steps by July 18th, when matriculated students were first eligible to register, and so received a later registration appointment, generally between August 1st and 3rd (the semester began August 17th). Within each of the three registration groups there were multiple registration appointments, spaced over consecutive weekdays from 9am to 2pm.

I primarily focused on courses that met Intersegmental General Education Transfer Curriculum (IGETC) requirements, which permits students to transfer from a community college to a California State University or University of California campus without the need, after transfer, to take additional lower-division, general education courses. Multiple courses satisfy an IGETC requirement (e.g., Biology, Anatomy, Physiology all meet the biological sciences requirement), and each course may offer multiple course sections at different times each semester. I also examined courses that met the A to G general education requirements for earning an Associate's degree, but omit these from the article as they overlapped significantly with IGETC courses but were consistently less crowded, such that IGETC provided a "worst-case scenario" for issues of overcrowding. Given that most awards earned at the community college were either Associate degrees or transfer certification, examining these areas provided, at a minimum, a good proxy for the level of overcrowding at the college.

Delay was defined as the number of minutes between a student's assigned registration time and their first registration attempt. Due to technical reasons related to the data, I only included students whose first registration attempt occurred before the semester started, which eliminated 11.2% of the study sample.³ The main analyses defined intensity as total registration attempts, which included any attempt to join or drop an open section, closed section, or wait-list, plus any "weak" attempts (e.g., attempts rejected due to time conflicts, not having met the minimum course requirements). This measure serves as a natural proxy for search, in part as the computer interface for student registration did not include information about wait-lists unless a student attempted to register in the closed course section. For robustness I later included four additional proxies: total registration attempts excluding drops and "weak" attempts, total distinct hours attempting to register across the entire registration period (consecutive hours counted as one attempt), total number of registration attempts in distinct courses, and registration attempts

in distinct course sections (e.g., attempting to register in three different sections of the same course counted as three attempts). Correlations between all five measures ranged from 0.57 to 0.95.

The remainder of the article proceeds as follows: First, I describe patterns related to assigned registration appointments and seat availability through the registration process. I then measure the extent to which delay and intensity were related within individuals, and what individual-level characteristics were predictive of shorter delay and higher intensity. Finally, I explore the extent to which these factors were predictive of students' academic outcomes in times of course scarcity. Implications are discussed in the concluding section.

Results

Assessing Course Capacity

Prior to 2008 about half of all available course sections closed at some point during the registration process, but the recession led this figure to spike dramatically, rising to 80% by fall 2010. Figure 1 maps out the percentage of available seats as of midnight each day, in four select IGETC areas during the Fall 2011–12 semester. The first three vertical lines indicate when most second semester, matriculated, and nonmatriculated students were first eligible to register, and the last line indicates the beginning of the fall semester. The percentage of seats available in Figure 1 should be interpreted as worst case scenarios for two reasons. First, I was only able to determine maximum seat capacity in course sections that became full (e.g., at least one student attempt to register and was rejected or required to join the wait-list). As this constituted anywhere from 98% of all biological sciences sections to 89% of humanities sections, I included only data from closed sections in Figure 1 with little loss of generality. Second, some course sections had artificially low capacity constraints as a percentage of seats were reserved for special groups that required permission to register, and so expanded beyond my capacity estimates. This was seen most clearly among Social and Behavioral Science sections, which went beyond my estimated capacity close to the beginning of the semester, but did not significantly affect most areas.

The primary takeaway from Figure 1 is that there is significant variability in the types of courses that were available to students. Students entering their second semester had access to courses in a large number of key areas, though limited access to seats in math or biological sciences. Matriculated new students, of which there were approximately

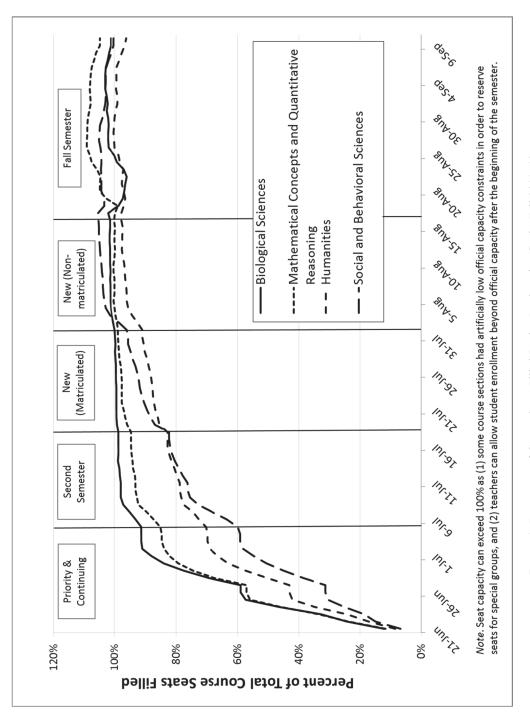


FIGURE 1. Percentage of Course Seats Filled During Registration Cycle, Fall 2011-12

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1,500, initially had access to approximately 150 and 30 seats in math and biological sciences, respectively, but more than 4,700 seats remained open in IGETC courses related to arts, humanities, social and behavioral sciences, and physical sciences. Nonmatriculated students, of which there were more than 3,000, had fewer options, with almost no seats in math and biological science, and a little over 2,100 seats in the remaining transfer areas. (Remedial math courses one or two levels below college math were similarly impacted, but remedial English courses had significant availability.) Even though some key areas had available seats, not all course sections should be considered similarly. Sections that closed earlier in the registration cycle had a stronger concentration of continuing students with higher GPAs, as well as more experienced teachers. Course sections with later closures were more likely to have new students, be located in satellite branches off the main campus, meet one day a week (three days per week courses were most popular), and were more frequently at 8am or after 4pm (10am and 11am were the most popular time slots).

Elements of Figure 1 highlight additional complexities in student registration. Overall, I found that conceptualizing registration as a straightforward process of receiving a registration date, entering the system, selecting courses, and taking those courses, would be a misunderstanding of how registration functions in practice. I briefly touch on three aspects here. First, there were large decreases in seat availability immediately after new groups were eligible to register, but the overall pattern was one of continuously declining availability over time. This occurred as many students did not optimally use their assigned registration time, waiting days or weeks before accessing the system (quantified in detail below). The second takeaway, though not well represented in Figure 1, is that students enrolled and dropped courses over and over again, leading to significant churn through the registration cycle. As a result of this churn, initial seat capacity was significantly lower than the total number of seats that later became available to students. As one illustrative example, of the students who were successfully enrolled in a course section when it first closed, only 68% were still enrolled in the course by the final drop date. Issues of delay and churn held for all registration groups and across all key course areas, as students enrolled in highly impacted IGETC courses dropped as frequently as other students.

The third point, also related to churn, was that course size fluctuated after the beginning of the semester. Courses expanded when teachers allowed excess students to enroll. This was seen most clearly among math courses, where the average section became, at its peak, about

10% larger than its official course capacity. Biological sciences, which exhibited the highest impaction during the initial registration process, also had the largest drop rates through the first two weeks of the semester. It bears noting that the figure only represents net drops, and so underestimates the total drop behavior as wait-listed and other students filled some of these seats. As a result of late drops, some areas operated below full capacity, even with teachers offering flexible classroom sizes.

Predictors of Delay and Intensity

The findings above suggest that students' registration behaviors are critically important to their academic progress. Students who registered on time had access to more courses, yet many closed courses did not stay full, as students frequently dropped and teachers created access. In this context, students who searched more intensely may have created additional opportunities to find available course seats. Table 1 provides characteristics of students in the three primary registration groups who had at least one registration attempt. I also included descriptive statistics for Matriculated students though, as noted above, I did not study their delay behaviors due to potential classification errors. Although most students who attempted to register took at least one course, 30% of nonmatriculated students took zero courses. Although overcrowding is theorized to negatively impact new students, matriculated students averaged more units than all other registration groups, even when examining IGETC and Associate degree general education courses which had significantly less availability later in the registration cycle. Nonmatriculated students attempted fewer units, but those students who took at least one course attempted almost as many IGETC and Associate degree units as students in their second semester.

Table 1 also illustrates that there was significant variation in delay and intensity profiles within each registration category, but student profiles looked relatively similar across categories. Students in the bottom delay quartile (e.g., those with the shortest delay) consistently registered within the first or second hour from initial access. Total registration attempts also looked similar across the three primary registration groups, with the least active quartile attempting five or fewer attempts, compared to twenty or more for the top quartile. Otherwise, I found that nonmatriculated students registered more quickly than other groups, though this may be due to right-censoring, as nonmatriculated students had a maximum of 16 days to register before the semester had begun and were excluded from my sample. Even with prior registration experience, one quarter of all continuing and second semester students waited more than two weeks before first attempting to register.

Nonmatriculated 2-6 (0.1-0.2) 7-48 (0.3-2) 8/1-8/3 0-1(0)%6.69 Matriculated 87.1% 12-23 24-47 1,535 7/18 1-11 3.1 4.9 9.6 3.6 5.6 29-358 (1.3-14.9) Second Semester 2-28 (0.1-1.2) 7/5-7/7 0-1(0)82.6% 12 - 226 - 1113,751 1-5 6.9 8.3 2.6 1-22 hours (0.1-0.9 days) 23-333 (1.0-13.9) 0 hours (0 days) Continuing 6/22-7/1 85.4% 10 - 1816,268 Course-Taking and Registration Characteristics, by Registration Group 5-9 1-4 7.1 8.3 Conditional On Taking At Least One Course: Primary Registration Appointments Delay to Register in Hours (Days): Total Registration Attempts: Fook At Least One Course Associate Degree Associate Degree 2nd quartile 2nd quartile 3rd quartile 1st quartile 3rd quartile 1st quartile Units Taken, Units Taken: IGETC IGETC TABLE 1 All All

1.5

9.9 2.2

Note. Quartiles may exceed one-quarter of the population as ties are placed in the lower category.

10 - 20

3,112

5-6

1-4

In order to examine the relationship between these two search qualities, I regressed intensity on delay, including registration appointment fixed-effects to compare students with identical appointment times (results not shown). I found a negative and statistically significant relationship between delay and search intensity, though the effect size was so small as to be considered practically insignificant. A delay of one full day was associated with 0.07 fewer registration attempts for continuing students and 0.12 fewer registration attempts for second semester students (p < 0.01), and there was no significant relationship for nonmatriculated students (results using alternate time frames and functional form assumptions produced similar results).

These results suggest that delay and intensity may constitute distinct behavioral qualities for the majority of students, and act as two separate avenues by which course-taking may be impacted. In order to understand which students were most likely to engage in these actions, I constructed linear probability models that regressed demographic, academic, and previous registration characteristics on the likelihood that a student was in the lowest delay quartile (Table 2, Columns 1–3) or the highest intensity quartile (Columns 4-6). Unfortunately, there was little available information for new students, especially as few nonmatriculated registrants had taken a math or English exam by the beginning of the semester. The little available data showed that new African American students were less likely to register on time (Column 1) and older students were less likely to be in the high-intensity group (Column 4).

Regressions for second semester and continuing students produced three main findings. Most importantly, students' individual-specific behaviors were consistently the strongest predictor for on-time registration or higher intensity. Second semester and continuing students who delayed the previous semester were between 12 and 20 percentage points less likely to be in the lowest delay quartile, and those with previously observed high intensity were over 20 percentage points more likely to stay in the highest intensity quartile. The second finding is that some students may have learned from previously unsuccessful registration experiences, though the evidence suggests that this occurred through increased attempts more often than better on-time registration. For example, students who had officially enrolled the previous semester but did not make a registration attempt or attempted to register but took no courses were significantly more likely to register intensely the following semester.

Finally, some demographic and academic characteristics were consistently associated with delay, but predictors of intensity produced mixed results. Students who were female, Asian, or had higher GPA were less

TABLE 2
Predictors of Delay and Intensity, by Registration Group

	Lc	Lowest Delay Quartile	ırtile	T	Fop Intensity Quartile	rtile
	New	Second Semester	Continuing	New	Second Semester	Continuing
Age	-0.001 (0.001)	0.001 (0.001)	-0.001* (0.000)	-0.007*** (0.001)	-0.004*** (0.001)	-0.001*** (0.000)
Female	0.026 (0.015)	0.076*** (0.014)	0.025*** (0.007)	-0.009	0.015 (0.013)	0.012 (0.006)
Asian	0.002 (0.030)	0.084***	0.048***	0.035 (0.030)	0.075***	0.019*
Latino	-0.038 (0.024)	-0.004 (0.021)	-0.003 (0.010)	0.045 (0.024)	0.039*	0.018 (0.010)
Black	-0.139*** (0.033)	-0.054* (0.027)	-0.018 (0.014)	0.046 (0.034)	0.040 (0.026)	0.059*** (0.014)
Ethnicity: Other	-0.036 (0.033)	0.045 (0.026)	0.032** (0.011)	0.063 (0.033)	0.074** (0.025)	0.030**
Ethnicity: Missing	-0.054** (0.019)	-0.038 (0.027)	-0.000 (0.015)	-0.082*** (0.020)	-0.008 (0.026)	0.021 (0.015)
Math: One Level Below College		-0.031 (0.031)	-0.044*** (0.010)		-0.034 (0.030)	0.022*
Math: Two or More Levels Below College		-0.059* (0.026)	-0.084*** (0.011)		-0.083*** (0.025)	-0.027* (0.010)
Math: No Record ^a		-0.085*** (0.024)	-0.098*** (0.010)		-0.082*** (0.023)	-0.028** (0.010)

TABLE 2 (continued)
Predictors of Delay and Intensity, by Registration Group

	Lowest Delay Quartile	artile		Top Intensity Quartile	ırtile
Z	New Second Semester	Continuing	New	Second Semester	Continuing
English: One Level Below College	-0.007 (0.034)	-0.068*** (0.019)		0.003 (0.033)	-0.006 (0.019)
English: Two or More Levels Below College	-0.041 (0.023)	-0.046*** (0.011)		0.038 (0.022)	-0.015 (0.011)
English: No Record ^a	-0.038* (0.020)	-0.062*** (0.009)		-0.072*** (0.019)	-0.055*** (0.009)
Cumulative GPA	0.033***	0.050*** (0.004)		-0.007 (0.007)	-0.012** (0.004)
No Calculated GPA♭	0.086** (0.027)			0.023 (0.026)	
Previous Semester Course-Taking					
Total units	0.004 (0.002)	0.008***		0.013***	0.012***
Did not attempt to register	-0.019 (0.035)	-0.171*** (0.017)		0.155***	0.119***
Attempted to register, took no course	0.049 (0.033)	0.011 (0.015)		0.063*	0.055***

(continued)

Predictors of Delay and Intensity, by Registration Group TABLE 2 (continued)

	Lo	Lowest Delay Quartile	urtile	To	Top Intensity Quartile	tile
	New	Second Semester	Continuing	New	Second Semester	Continuing
Previous Semester Delay and Intensity						
Second lowest delay quartile (Q2)		-0.141*** (0.023)	-0.183*** (0.010)		0.025 (0.022)	0.005 (0.009)
Delay Q3		-0.121*** (0.023)	-0.201*** (0.010)		0.043*	0.026** (0.010)
Delay Q4		-0.143*** (0.023)	-0.183*** (0.010)		0.045*	0.060***
Lowest intensity quartile (Q1)		-0.030 (0.023)	-0.021* (0.010)		-0.000 (0.022)	-0.029** (0.010)
Intensity Q3		0.058*	-0.002 (0.010)		0.058**	0.087***
Intensity Q4		0.092*** (0.024)	0.039***		0.220***	0.237***
Intercept	0.276*** (0.017)	0.336***	0.430*** (0.014)	0.308***	0.217*** (0.034)	0.153***
N Adjusted R-Squared	3,039	3,682	6,057 0.12	3,039 0.04	3,682 0.13	16,057 0.14

Note. All regressions include registration appointment fixed-effects. Students with missing data are removed from the analysis. The reference category is an 18-year-old white male student with a 2.5 GPA who took six units the previous semester, and was classified as D_1 , (i.e., the lowest delay quartile and in the second lowest intensity quartile).
*Students are missing math or English records if they have not yet taken either a placement exam or departmental course, but may have met these requirements outside the college or in high school. 6 GPA may not be calculated for second semester students who took courses ungraded or withdrew the previous semester. $^{***}p < 0.001. **p < 0.011. **p < 0.001. **p < 0.05.$

likely to delay, and students at lower levels of math or English or who had not yet attempted these courses were more likely to delay. Intensity results were more difficult to interpret, as continuing students two levels below college math exhibited less intensity than students one-level below college, but more intensity than students at college-level, even though all three math levels were found to be extremely impacted. I also found that students with higher GPA were less likely to be in the high intensity quartile. Overall, shorter delay might be considered an unambiguously positive step towards securing needed courses. Intensity could, at times, be lower for students with well-designed educational plans, so we must examine the empirical results to better understand intensity's relationship with course-taking.

Delay and Intensity as Predictors of Course Taking

To measure the association between search characteristics and academic outcomes, I ran the following regression:

$$Y_{i} = \left(\sum_{m=1}^{4} \sum_{n=1}^{4} \beta_{mn} D_{m} I_{n}\right) + X_{i} + \mu_{j} + \varepsilon_{i}$$
(1)

where Y are outcomes primarily focused on students course-taking patterns, D_m are dummies for each delay quartile, I_n are dummies for intensity quartile, X_i are a vector of individual-level characteristics, μ_i are absorbed fixed-effects for students' specific assigned registration time, and ε_i is an individual-level idiosyncratic error term. I chose this model to avoid making functional form assumptions regarding delay and intensity, as well as ease of interpretation as to the relative outcomes for these two qualities (e.g., Do students with long delay who engage in high intensity take more or less units than those with no delay with less intensity?). Unless otherwise noted, all regressions include individuallevel demographic characteristics of age, sex, and ethnicity. Academic (units attempted the previous semester, cumulative GPA, math and English level as determined by placement exams and course-taking) and behavioral (registration attempts the previous semester) controls are included in models that focus on continuing and second semester students. Registration assignment fixed-effects (μ_i) are included as a student's specific registration appointment was related to either GPA and length of time within the system (for continuing students) or how early a student first applied to the college (for new students), which were both correlated with course-taking behaviors. Thus all regressions estimated the relationship between delay, intensity, and outcomes strictly within each group of students with the same assigned registration appointment. All regressions used students classified as $D_I I_2$ as the omitted reference category; these were students in the lowest delay quartile (i.e., no delay, or generally registering within the first hour) and were in the second lowest quartile in terms of total registration attempts.

Figure 2A shows results from regressions that estimated the likelihood a student took at least one course. As expected, students who delayed longer or searched less intensely were less likely to take a course, but the negative impact of delay was much smaller for students in the high-intensity quartile than for students in the middle or low intensity quartiles (approximately 6 percentage points, compared to 13 and 18 percentage points, respectively). I found similar results when examining total units attempted (Figure 2B), with variation in registration intensity a stronger predictor of units attempted than simple delay. Even for students who did not delay, higher intensity was associated with a higher number of units attempted, such that there may be payoffs to engaging in extra registration attempts rather than selecting the first available classes.

Table 3 shows additional results for units attempted in courses related to Associate degree general education and IGETC requirements, including the four IGETC subcategories highlighted in Figure 1. For simplicity, I only report regression coefficients for students in the bottom and top intensity quartiles, as middle quartile students always lie between these two groups and exhibit identical delay patterns (full results available in Appendix A). I found penalties for longer delay and lower intensity for each course-taking outcome, with the largest negative outcomes reserved for students who exhibited the lowest search intensity. Students with long delay who exhibited the highest search intensity (D_4I_4) had outcomes that were often similar or only slightly below the omitted category of students who did not delay but showed lower levels of intensity, with the largest negative differences in IGETC units (Table 3, Column 4), especially as it related to biological sciences (Column 8).

Table 4 investigates the relationship among delay, intensity, and outcomes within each of the three registration groups. I focused on students' total units attempted, as examination of other areas produced similar results. (Appendix B and C provide full results for total and IGETC units attempted.) In a model with no individual-level controls, continuing students who delayed the longest but had the highest intensity (D_4I_4) took approximately one fewer unit than the baseline category of students with less intensity but no delay (Table 4, Column 1). In

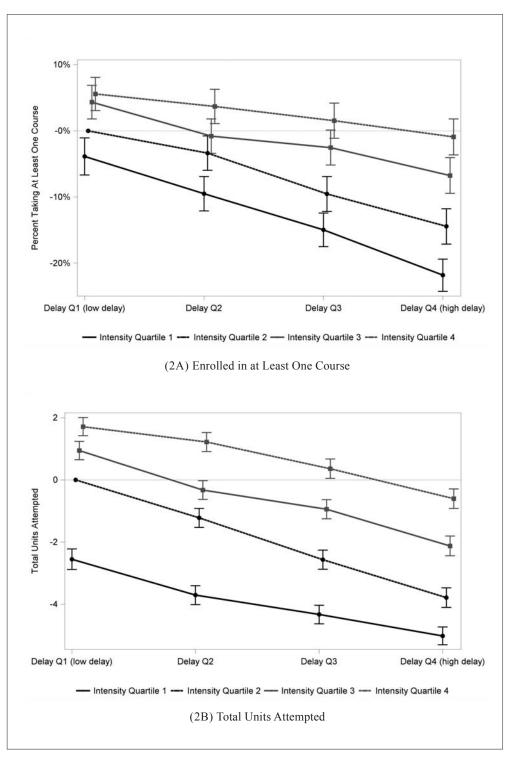


FIGURE 2. Academic Outcomes, by Student Delay and Intensity

Academic Outcomes, by Search Delay and Intensity TABLE 3

						IGETC S ₁	IGETC Subcategories	
	Took a Course	Total Units	Associate Degree IGETC Units Units	IGETC Units	Math	Humanities	Social Science	Biological Science
Intensity Quartile 1 (Least Intense Search)								
Delay Quartile 1 (D,I) (Shortest Delay)	-0.039** (0.014)	-2.556*** (0.168)	-1.459*** (0.137)	-1.362*** (0.124)	-0.212*** (0.056)	-0.151*** (0.033)	-0.267*** (0.061)	-0.246*** (0.042)
Delay Q2 (D_2I_j)	-0.096*** (0.013)	-3.717*** (0.156)	-2.151*** (0.127)	-1.936*** (0.115)	-0.417*** (0.052)	-0.184*** (0.031)	-0.447*** (0.056)	-0.319*** (0.039)
Delay Q3 (D_3I_j)	-0.150*** (0.013)	-4.340*** (0.151)	-2.478*** (0.123)	-2.219*** (0.112)	-0.489*** (0.050)	-0.215*** (0.030)	-0.503*** (0.055)	-0.396*** (0.038)
Delay Q4 $(D_j I_j)$ (Longest Delay)	-0.219*** (0.012)	-5.027*** (0.146)	-2.848*** (0.119)	-2.410*** (0.108)	-0.618*** (0.049)	-0.243*** (0.029)	-0.578*** (0.053)	-0.414*** (0.037)
Intensity Q2 and Q3 (omitted)			I	I	I	I		I
Intensity Q4 (Most Intense Search)								
Delay Q1 $(D_l I_l)$	0.056***	1.722*** (0.150)	1.477*** (0.122)	1.167*** (0.111)	0.420***	0.033 (0.030)	0.201*** (0.054)	0.223*** (0.038)
Delay Q2 (D_2I_2)	0.037** (0.013)	1.223*** (0.156)	0.974*** (0.127)	0.548***	0.305*** (0.052)	-0.023 (0.031)	0.239***	-0.077 (0.039)
Delay Q3 (D_3I_i)	0.016 (0.014)	0.365* (0.159)	0.289* (0.129)	-0.142 (0.117)	0.211***	-0.032 (0.031)	0.073 (0.057)	-0.168*** (0.040)
Delay Q4 $(D_{\downarrow}I_{\downarrow})$	-0.009 (0.014)	-0.604*** (0.162)	-0.340** (0.132)	-0.725*** (0.120)	-0.172** (0.054)	-0.101** (0.032)	-0.037 (0.059)	-0.274*** (0.041)
Intercept	0.936***	9.626*** (0.127)	4.574*** (0.094)	5.429*** (0.103)	1.009*** (0.042)	0.455*** (0.025)	1.043*** (0.046)	0.554*** (0.032)
	22,851	22,851	22,851	22,851	22,851	22,851	22,851	22,851
					٠			

Note. All regressions include registration appointment fixed-effects and demographic (age, sex, ethnicity) controls. The reference category are students classified as $D_j I_j$ (i.e., the lowest delay quartile and in the second lowest intensity quartile).

***p < 0.001. **p < 0.001. **p < 0.001. **p < 0.05.

Total Units Attempted, by Registration Group TABLE 4

	Continuing	nuing	Second Semester	Semester	New	M.
Intensity Quartile 1 (Least Intense Search)						
Delay Quartile 1 (D, I_j) (Shortest Delay)	-3.401*** (0.209)	-1.859*** (0.186)	-2.260*** (0.437)	-1.249** (0.397)	-1.939*** (0.413)	-1.526*** (0.372)
Delay Q2 $(D_{\beta}I_{i})$	-4.864*** (0.190)	-2.869*** (0.172)	-3.918*** (0.402)	-2.779*** (0.369)	-2.203*** (0.401)	-1.879*** (0.362)
Delay Q3 (D_jI_j)	-5.598*** (0.182)	-3.336*** (0.166)	-4.307*** (0.392)	-3.082*** (0.359)	-3.002*** (0.409)	-2.230*** (0.368)
Delay Q4 $(D_j I_j)$ (Longest Delay)	-6.473*** (0.175)	-3.977*** (0.162)	-4.732*** (0.374)	-3.598*** (0.346)	-2.813*** (0.402)	-2.525*** (0.361)
Intensity Q2 and Q3 (omitted)		1	-	-	l	
Intensity Q4 (Most Intense Search)						
Delay QI (D_lI_l)	1.726*** (0.181)	0.898***	2.456*** (0.397)	1.268*** (0.363)	2.595*** (0.410)	2.065*** (0.368)
Delay Q2 $(D_j I_j)$	1.079*** (0.189)	0.437** (0.169)	2.694*** (0.403)	1.493*** (0.369)	2.270*** (0.422)	1.904*** (0.379)
Delay Q3 (D_3I_4)	0.094 (0.191)	-0.215 (0.171)	1.319** (0.417)	0.781*	2.234*** (0.433)	1.569*** (0.392)
Delay Q4 $(D_j I_j)$	-0.943*** (0.195)	-0.740*** (0.175)	0.427 (0.439)	0.250 (0.404)	1.611*** (0.429)	1.111**
Student Controls ^a	Z	Y	Z	X	Z	>
Intercept	9.090*** (0.132)	8.078*** (0.163)	7.859*** (0.288)	9.101*** (0.422)	4.994*** (0.311)	6.685***
N	16,268	16,057	3,751	3,682	3,112	3,039

Note. All regressions include registration appointment fixed-effects. The reference category are students classified as $D_i I_j$ (i.e., the lowest delay quartile and in the second lowest intensity quartile).

*Student controls includes demographics (age, sex, and ethnicity), academics (math and English levels, cumulative GPA, units taken the previous semester), and behavioral (previous delay and intensity measures). New students do not have academic or behavioral controls.

****p < 0.001. ***p < 0.01. **p < 0.05.

contrast, the same comparison for second semester students found no statistical differences in units attempted (Column 3), and long-delay, high-intensity new students actually took more units than their peers who did not delay but showed less intensity (Column 5). These results held after controlling for all available demographic, academic, and previous registration characteristics (Columns 2, 4, and 6). At the extreme end, inclusion of controls decreased the magnitude of the delay and intensity coefficients by approximately one-half, but all statistically significant relationships remain unchanged. These results show that new students who registered immediately and searched intensely averaged over twice as many units as those in the bottom delay and intensity quartiles (8.8 units compared to 4.2 units, respectively).

These results indicate that some students, even those with long delays, used persistent registration efforts as a tool to overcome course closures. These efforts may have been most effective for new students, perhaps as they have more flexibility in the types of courses they can take to meet degree goals, whereas continuing students who delay might be locked out of specific courses with no real alternatives. It bears noting that even though high-intensity new students took more units compared to their peers, they still took low levels of units overall in overcrowded IGETC subcategories. Even in the best scenario, high-intensity, new students took a course meeting the biological sciences requirement about one-third as often as continuing students.

As total number of registration attempts is just one proxy for search intensity, Table 5 predicted total units attempted with four alternate intensity indicators. The basic findings were robust to the utilization of different intensity metrics.⁴ Although total registration attempts is the most straightforward metric for examining search intensity, the total number of distinct courses in which a student attempted to register was a stronger predictor of units attempted, followed closely by total number of distinct sections. Students with long delays who took the time to examine more distinct courses attempted more units than our reference category students, an even stronger finding that earlier regressions using total registration attempts as the intensity proxy. Examining more distinct courses was also associated with smaller delay penalties for IGETC units and other outcomes (results not shown). Total number of distinct hours on the systems appears to be the weakest predictor, with both lower adjusted R-squared and results that are, on average, more anomalous to the other four metrics. Taken together, these results suggest that specific search strategies, including a willingness to take courses that were not considered a first option, has positive payoffs for students

Total Units Attempted, by Intensity Proxies TABLE 5

	Total Registration Attempts	Adjusted Registration Attempts	Registration Hours	Distinct Course Attempts	Distinct Section Attempts
Intensity Quartile 1 (Least Intense Search)					
Delay Quartile 1 $(D_i I_i)$ (Shortest Delay)	-2.556*** (0.168)	-3.287*** (0.155)	-0.324 (0.170)	-3.620*** (0.157)	-3.684*** (0.160)
Delay Q2 $(D_2 I_i)$	-3.717*** (0.156)	-3.947*** (0.141)	-2.015*** (0.169)	-4.205*** (0.143)	-4.406*** (0.147)
Delay Q3 $(D_{i}I_{i})$	-4.340*** (0.151)	-4.288*** (0.135)	-3.121*** (0.169)	-4.523*** (0.135)	-4.739*** (0.141)
Delay Q4 $(D_{i}I_{i})$ (Longest Delay)	-5.027*** (0.146)	-4.897*** (0.133)	-4.355*** (0.166)	-4.923*** (0.128)	-5.326*** (0.136)
Intensity Q2 and Q3 (omitted)	I	I	I	I	I
Intensity Q4 (Most Intense Search)					
Delay Q1 (D_lI_l)	1.722*** (0.150)	2.629*** (0.141)	2.070*** (0.182)	3.062*** (0.146)	2.260*** (0.151)
Delay Q2 (D_2I_4)	1.223*** (0.156)	2.169*** (0.150)	1.414*** (0.185)	2.565*** (0.150)	1.821*** (0.156)
Delay Q3 $(D_i I_i)$	0.365*	1.160*** (0.152)	0.880*** (0.185)	1.715*** (0.153)	0.884*** (0.159)
Delay Q4 $(D_j I_j)$	-0.604*** (0.162)	-0.123 (0.151)	0.189 (0.196)	0.773*** (0.157)	-0.249 (0.165)
Intercept	9.626*** (0.127)	8.973*** (0.111)	9.349*** (0.153)	8.671*** (0.110)	9.266*** (0.121)
N Adjusted R -squared	22,851 0.32	22,851 0.37	22,851 0.29	22,851 0.42	22,851 0.39

Note. All regressions include registration appointment fixed-effects and demographic (age, sex, ethnicity) controls. The reference category are students classified as $D_j I_j$ (i.e., the lowest delay quartile and in the second lowest intensity quartile).

***p < 0.001. **p < 0.001. **p < 0.001. **p < 0.05.

Finally, I examined whether delay and intensity also predicted the likelihood of returning to the college the subsequent semester. I found that students with shorter delay were more likely to return the following semester, which conforms with previous research, as were those with higher intensity (Figure 3A). Perhaps due to data issues, previous work on registration has not examined whether delayed registration is associated with fewer units attempted, which may serve as a mediating variable for the likelihood of returning. For example, unadjusted means indicated that only 13.3% of new students who took no units returned to the college the following semester, and this value rose linearly to 80.0% for students who took 15 units (results are similar for continuing and second semester students). Students who took no courses might quickly become disengaged from the academic or social systems of the college (Tinto, 1975), and quickly drop out. Figure 3B shows retention rates to the following semester but added one additional predictor—total units attempted in the current semester—to our model for Figure 3A. As a result, most of the differences in retention due to delay and intensity were eliminated. I still found that being in the highest delay quartile was associated with a decrease in persistence of approximately 5 percentage points, though this was significantly reduced from an estimated effect difference of approximately 20 percentage points in our model that adjusted for demographic controls. Table 6 shows that results held in models that included only second semester and continuing students and controlled for academic and behavioral characteristics, as well as separate models for new students. The results were unchanged when examining longer-term persistence to the subsequent school year (not shown).

Discussion

This analysis of one community college provided a much more complex picture of overcrowding and student registration than is normally described by media or policy reports. I found that the community college was indeed "overcrowded," as almost every section became full and most courses in key areas had long wait-lists. Yet policy narratives that describe continuing students as monopolizing the available opportunities miss a substantial portion of the puzzle, as students varied significantly in how long they delayed before first registering and how intensely they looked for courses. As a result, many key course areas had some availability during the registration process, though specific areas, such as math and biological sciences, were initially unavailable to most new students. In addition, significant churn and expanded

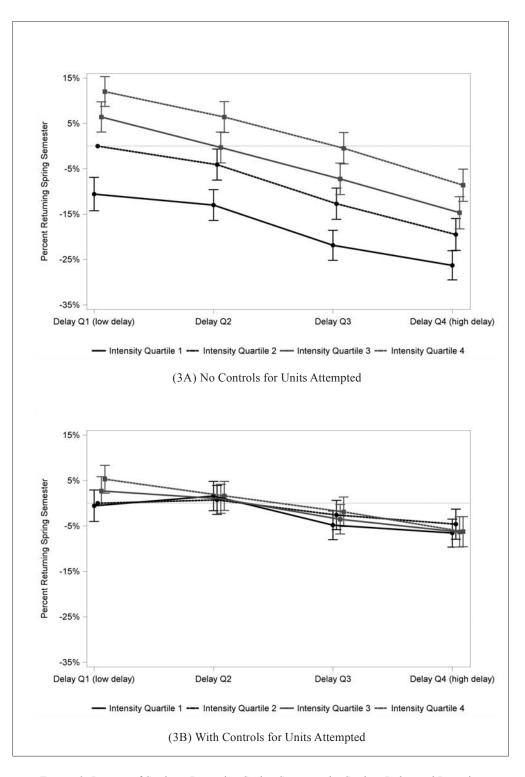


FIGURE 3. Percent of Students Returning Spring Semester, by Student Delay and Intensity

(0.045)-0.012 (0.044) -0.056 (0.045)-0.016 (0.044) 0.075 (0.045) -0.022 (0.046) -0.029 (0.047) -0.019 (0.047) 0.151** (0.047) -0.138** (0.047) New -0.109* (0.046) (0.047)(0.046)0.048 (0.048) 0.029 (0.050) -0.0540.022 (0.049) -0.0810.190*** (0.049) -0.194*** -0.133** (0.048) -0.095* (0.049)(0.048)(0.049)0.050 (0.051) 0.070 (0.052) 0.044 (0.051) -0.059*** 0.049** (0.017) -0.044* -0.046* (0.018) (0.019)(0.018)(0.017)(0.017)(0.017)-0.007 (0.018) -0.0120.032 0.021 Continuing / Second Semester -0.165*** (0.018) -0.201*** (0.017) 0.087*** (0.018) -0.065*** (0.019) -0.075*** -0.083*** 0.058** (0.020)(0.019)-0.007 (0.019) Percent Returning Spring Semester, by Registration Group -0.291*** (0.017) -0.103*** (0.019) -0.135***-0.230*** (0.018) 0.112*** (0.018) 0.071*** -0.111*** (0.020)(0.019)-0.015 (0.019) (0.018)Intensity Quartile 1 (Least Intense Search) Intensity Q4 (Most Intense Search) Intensity Q2 and Q3 (omitted) Delay Quartile 1 (D_II_I) (Shortest Delay) (Longest Delay) Delay Q4 (D_tI_l) Delay Q2 (D_2I_l) Delay Q3 (D_3I_I) Delay Q1 (D_II_4) Delay Q2 (D_2I_4) Delay Q3 (D_3I_4) Delay $\mathbb{Q}4 \; (D_t I_t)$ TABLE 6

TABLE 6 (continued)
Percent Returning Spring Semester, by Registration Group

	Con	Continuing / Second Semester	emester		New	
Student Controls ^a	Z	Y	7	¥	Y	¥
Control for Units Attempted	Z	Z	Y	Y	Z	Y
Intercept	0.736***	0.687***	0.403***	0.428***	0.551***	0.305***
N	20,019	19,812	19,812	3,112	3,039	3,039
Note. All regressions include registration appointment fixed-effects. The reference category are students classified as D.I. (i.e., the lowest delay quartile and in the second	ment fixed-effects.	The reference cate	gory are students class	ified as D,L, (i.e., the	lowest delay quart	ile and in the second

Note. All regressions include registration appointment fixed-effects. The reference category are students classified as $D_L J_c$ (i.e., the lowest delay quartile and in the second lowest intensity quartile). Student controls includes demographics (age, sex, and ethnicity), academics (math and English levels, cumulative GPA, units taken the previous semester), and behavioral (previous delay and intensity measures). New students do not have academic or behavioral controls. ***p < 0.001. **p < 0.001.

course sections provided extra opportunities for students to enroll in high-demand courses. I found that new students who fully matriculated took more units, on average, than students who had been enrolled two or more semesters within the system, and nonmatriculated in the top registration quartiles students attempted over twice as many units as nonmatriculated students in the bottom quartiles. This connection to the college was found to be vitally important, as almost all differences in retention rates associated with delay or intensity became insignificant after controlling for units attempted.

These findings suggest that both individual-level and institutionallevel actions should be considered when addressing the allocation of scarce course offerings. It is likely that some of the variation in search behaviors reflects weaker commitment to pursuing a college education, as observed by the correlation between long delay and lower prior academic performance. This variation may also reflect a lack of knowledge about the community college application or registration process, the role of persistence and course auditing in gaining access to closed courses, or how to construct optimal course schedules. This may be particularly pertinent to new students, as approximately 30% of nonmatriculated students took no courses and most did not return to the college. Better linkages between community colleges and their local K-12 partners are vital towards smoothing this challenging transition, especially for first-generation college students. Yet I found that significant numbers of continuing students, even those with strong academics and abundant familiarity with the registration process, continued to procrastinate before beginning the registration process, and many engaged in substantially weaker registration attempts.

Formally introducing the concept of present-bias into students' registration behaviors serves two purposes. First, research has shown that procrastination affects all types of individuals and may be improved with the appropriate structures in place, and it would be incorrect to assume that students who exhibit longer delay or lower search intensity are necessarily ill-suited for the college environment. Second, lessons from previous studies of procrastination can provide colleges guidance on how to alter registration systems to improve behaviors. Shortening the registration process and moving it closer to the beginning of the semester decreases the timeline between present costs and future rewards, potentially making the payoffs to registration more tangible. Simplifying the complex registration process could reduce "hassle costs" that may appear minimal but can have an impact on the timely completion of tasks (Baicker, Congdon, & Mullainathan, 2012). As one example, improved technologies could reduce hassle costs and prevent issues

related to choice overload by helping students focus on high-priority courses based on their stated goals, time preferences, or past behaviors, and automatically offering alternate sections or courses when initial attempts fail. Students might also register more effectively through highfrequency reminders and incentives (Babcock, Congdon, Katz, & Mullainathan, 2012), which could take the form of simple text or email messages (Castleman & Page, 2013), to more powerful financial incentives, such as lotteries that give tuition rebates to randomly drawn students who register early (Volpp et al., 2008) (and may be worthwhile if earlier registration improves a college's enrollment management process). Of course, improved counseling services and providing better information may help decision-making, especially as students may underestimate the benefits of engaging in additional search activities (Spinnewijn, 2013), though California cut categorical funding for matriculation services by half during the recession (Taylor, 2010). Some of these approaches might be counterproductive if students who register early do so without an increase in their commitment to the schedule, as students currently drop courses at a high rate. Creating penalties for dropping courses might be unpalatable for many colleges, though restrictive interventions that help bring a student's short-run decisions more in line with their long-run preferences may improve self-control and individual welfare (Paserman, 2008). Precommitment devices, such as providing earlier access to students conditional on losing access after a specified number of days, or requiring students to pay for classes upon registration (as opposed to by the final drop date), may paradoxically help students make better registration decisions.

Taken as a whole, this study showed that some students were able to overcome institutional constraints through early completion of matriculation steps, utilizing their registration time effectively, and being persistent in the face of course closures. In addition, many of the roadblocks in the system appeared temporary, as students had exponentially more access after only one semester within the system. Although not the focus of this article, simple estimates that take into account delayed registration, churn, and other factors, found that students California deems as "high-unit" or "low academics"—who will be moved to the back of the registration line by new policies—occupied only 100 to 200 seats in the most impacted courses, and their removal was unlikely to make a significant impact on the likelihood that new students have sufficient spots available. The current registration structure already favors those students who take the steps to navigate community college matriculation significantly in advance of the beginning of the semester, understand how and are willing to select alternative or less desirable courses

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to meet short-term goals, are free to sit in multiple classes early in the semester in anticipation of late openings, and, in the worst case scenario, can afford to stay-or even waste-a semester or two to earn enough credits that would allow them to get into the courses they need. In informal conversations with students, they described showing up to a course and waiting for others students to drop (or to be dropped by the instructor for failing to show) as the most common method for enrolling in oversubscribed courses, and these types of actions may serve as the key mechanism as much as persistent computer-based registration attempts. Students who have less familiarity with how the college system works, need to enroll part-time, have limited availability due to family or financial considerations, or are unsure of their postsecondary goals, may be further disadvantaged by proposed changes to registration priorities. History suggests that this second type of student may be much more common within the community college system (Goldrick-Rab, 2010; Rosenbaum et al., 2006; Scott-Clayton, 2011).

Although understanding students' registration behaviors provides a stronger framework for analyzing policies that might restructure the allocation of resources to students, altering these behaviors will only be beneficial if sufficient resources exist to satisfy the aggregate demand facing the system. One particular area of concern are the most impacted courses—math and biological sciences—which are needed by thousands of incoming students. One way to increase capacity would be to shift resources from relatively undersubscribed courses into these areas, which would require more sophisticated course management systems for colleges. Colleges must also elucidate the constraints that prevent them from offering more sections in the most oversubscribed areas. For example, if the key constraint is teacher labor supply, California could approve an emergency credential to allow high school teachers with math or science skills to teach in community colleges without a Master's degree. For community colleges that lack facilities—conversations with school staff cited this as an ongoing technical challenge—localities should develop short-term contracts that make unused city-owned spaces available to colleges. More dialogue between community colleges, their localities, and the state, could help produce increased efficiencies in an era of diminished resources.

Notes

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- grant #R305B090016 from the U.S. Department of Education, Institute of Education Sciences.
- ¹ For brevity this section omits many details regarding the registration system which are inconsequential to the analysis.
- ² Although the registration behaviors of both groups are of interest, there were concerns about the accuracy of the delay variable for the matriculated group, as 18% first attempted to register almost two weeks after the assigned registration time; in all three other groups this value ranged from 1 to 3%. The most likely explanation is that some nonmatriculated students were misclassified as matriculated students. Inclusion of these anomalous students in the nonmatriculated category does not alter the results, but I choose to omit these students altogether for simplicity.
- ³ In this college's data system, registration attempts after the beginning of the semester were predominately successful as they occurred most often when students secured course permission codes from teachers or enrolled from the wait-list, both of which occurred through persistent individual efforts. Students with early registration times whose first registration attempt was after the semester were actually a highly-select subset that were generally more successful than other students who had shorter registration delays.
- ⁴ All regressions included controls for student demographics. Regressions for continuing and second semester students that controlled for academic and behavioral characteristics produced similar results, and are available on request.

References

- Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. Psychological Bulletin, 82(4), 463-496.
- Aud, S., Hussar, W., Johnson, F., Kena, G., Roth, E., Manning, E., et al. (2012). The condition of education 2012. Washington DC: U.S. Department of Education, National Center for Education Statistics.
- Babcock, L., Congdon, W. J., Katz, L. F., & Mullainathan, S. (2012). Notes on behavioral economics and labor market policy. IZA Journal of Labor Policy, 1(2), 1–14.
- Bahr, P. R., Gross, J. L., Slay, K. E., & Christensen, R. D. (2014). First in line: Student registration priority in community colleges. Educational Policy. Advance online publication. doi: 10.1177/0895904813492381
- Baicker, K., Congdon, W. J., & Mullainathan, S. (2012). Health insurance coverage and take-up: Lessons from behavioral economics. The Milbank Quarterly, 90(1), 107–134.
- Baum, S., & Ma, J. (2012). Trends in college pricing 2011. New York: College Board Advocacy and Policy Center.
- Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. Chicago: University of Chicago Press.
- Bettinger, E., & Slonim, R. (2007). Patience among children. Journal of Public Economics, 91(1-2), 343-363.
- Bohn, S., Reyes, B., & Johnson, H. (2013). The impact of budget cuts on California's community colleges. San Francisco: Public Policy Institute of California.
- Bound, J., Lovenheim, M. F., & Turner, S. E. (2010). Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. American Economic Journal: Applied Economics, 2(3), 129–157.

- Bound, J., & Turner, S. (2007). Cohort crowding: How resources affect collegiate attainment. *Journal of Public Economics*, 91, 877–899.
- Bryant, D., Danley, J., Fleming, S., & Somer, P. (1996). "The dog ate it" and other reasons why students delay registration. *College and University*, 71(4), 2–8.
- California Community Colleges Student Success Task Force. (2012). Advancing student success in California community colleges: The recommendations of the California Community Colleges Student Success Task Force. Sacramento, CA: California Community Colleges Chancellor's Office.
- Castleman, B. L., & Page, L. C. (2013). Can text messages mitigate summer melt? New England Journal of Higher Education, May 2013.
- DellaVigna, S., & Paserman, M. D. (2005). Job search and impatience. *Journal of Labor Economics*, 23(3), 527–588.
- Ford, G. G., Stahl, K. J., Walker, M. E., & Ford, A. M. (2008). Better late than never? The relation of registration date to class performance. *College Student Journal*, 42(2), 402–407.
- Gardner, L. (2012, August). Survey of California community colleges reveals drastic effects of budget cuts, *The Chronicle of Higher Education*. Retrieved from http://chronicle.com/article/Survey-of-California-Community/134020/
- Goldrick-Rab, S. (2010). Challenges and opportunities for improving community college student success. *Review of Educational Research*, 80(3), 437–469.
- Hagedorn, L. S., Maxwell, W. E., Cypers, S., Moon, H. S., & Lester, J. (2007). Course shopping in urban community colleges: An analysis of student drop and add activities. *The Journal of Higher Education*, 78(4), 464–485.
- Hale, J. M., & Bray, N. J. (2011). The impact of registration timing on student performance. *Community College Journal of Research and Practice*, *35*, 556–573.
- Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Personality Processes and Individual Differences*, 79(6), 995–1006.
- Kane, T. J., & Orszag, P. R. (2003). Funding restrictions at public universities: Effects and policy implications. Washington DC: Brookings Institution.
- Kurlaender, M., Jackson, J., Howell, J. S., & Grodsky, E. (2012). *College course scarcity and time to degree*.
- Little Hoover Commission. (2012). Serving students, serving California: Updating the California community colleges to meet evolving demands. Sacramento, CA: Milton Marks Commission on California State Government Organization and Economy.
- O'Donoghue, T., & Rabin, M. (2001). Choice and procrastination. *Quarterly Journal of Economics*, 116(1), 121–160.
- Oliff, P., Palacios, V., Johnson, I., & Leachman, M. (2013). Recent deep state higher education cuts may harm students and the economy for years to come. Washington, DC: Center on Budget and Policy Priorities.
- Paserman, M. D. (2008). Job search and hyperbolic discounting: Structural Estimation and Policy Evaluation. *The Economic Journal*, *118*(531), 1418–1452.
- Pearson Foundation. (2011). Pearson Foundation community college student survey: Summary of California results. Retrieved from http://pearsonfoundation.org/downloads/CC_Student_Survey_California.pdf

- Rosenbaum, J. E., Deil-Amin, R., & Person, A. E. (2006). After admission: From college access to college success. New York: Russell Sage Foundation.
- Safer, A. M. (2009). The effect of late registration for college classes. College Student Journal, 43(4), 1380-1388.
- Schouwenburg, H. C. (1995). Academic procrastination: Theoretical notions, measurement, and research. In J. R. Ferrari, J. L. Johnson & W. G. McCown (Eds.), Procrastination and task avoidance: Theory, research, and treatment (pp. 71-96). New York:
- Scott-Clayton, J. (2011). The shapeless river: Does a lack of structure inhibit students' progress at community colleges? (CCRC Working Paper No. 25). New York: Community College Research Center, Columbia University.
- Smith, A. B., Street, M. A., & Olivarez, A. (2002). Early, regular, and late registration and community college success: A case study. Community College Journal of Research and Practice, 26(3), 261-273.
- Spinnewijn, J. (forthcoming). Unemployed but optimistic: Optimal insurance design with biased beliefs. Journal of the European Economics Association.
- Stange, K. (2012). Ability sorting and the importance of college quality to student achievement: Evidence from community colleges. Education Finance and Policy, 7(1), 74–105.
- Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. Psychological Bulletin, 133(1), 65–94.
- Taylor, M. (2010). The 2010-11 budget: Higher education. Sacramento, CA: Legislative Analyst's Office.
- Taylor, M. (2011). The 2011–12 budget: Prioritizing course enrollment at the community colleges. Sacramento, CA: Legislative Analyst's Office.
- Taylor, M. (2012). The 2012–13 budget: Analysis of the governor's higher education proposal. Sacramento, CA: Legislative Analyst's Office.
- Tinto, V. (1975). Dropout from Higher Education: A Theoretical Synthesis of Recent Research. Review of Educational Research, 45(1), 89–125.
- Turner, S. E. (2004). Going to college and finishing college: Explaining different educational outcomes. In C. M. Hoxby (Ed.), College Choices: The economics of where to go, when to go, and how to pay for it (pp. 13–62). Chicago: National Bureau of Economic Research, University of Chicago Press.
- Varlotta, L. (2010). Enrollment management in the CSU: Right-Sizing to align with state allocations. Enrollment Management Journal, 4, 116-136.
- Venezia, A., Kirst, M. W., & Antonio, A. (2003). Betraying the college dream: How disconnected K-12 and postsecondary education systems undermine student aspirations. Stanford, CA: Stanford Institute for Higher Education Research.
- Volpp, K. G., Loewenstein, G., Troxel, A. B., Doshi, J., Price, M., Laskin, M., & Kimmel, S. E. (2008). A test of financial incentives to improve warfarin adherence. BMC Health Services Research, 8(272), 1-6.

APPENDIX A
Academic Outcomes, by Search Delay and Intensity

						IGETC	IGETC Subcategories	
	Took a Course	Total Units	Associate Degree Units	IGETC Units	Math	Humanities	Social Science	Biological Science
Intensity Quartile 1 (Least Intense Search)								
Delay Quartile 1 $(D_l I_l)$ (Shortest Delay)	-0.039** (0.014)	-2.556*** (0.168)	-1.459*** (0.137)	-1.362*** (0.124)	-0.212*** (0.056)	-0.151*** (0.033)	-0.267*** (0.061)	-0.246*** (0.042)
Delay Q2 $(D_2 I_j)$	-0.096*** (0.013)	-3.717*** (0.156)	-2.151*** (0.127)	-1.936** (0.115)	-0.417*** (0.052)	-0.184*** (0.031)	-0.447*** (0.056)	-0.319*** (0.039)
Delay Q3 (D_3I_i)	-0.150*** (0.013)	-4.340*** (0.151)	-2.478*** (0.123)	-2.219*** (0.112)	-0.489*** (0.050)	-0.215*** (0.030)	-0.503*** (0.055)	-0.396*** (0.038)
Delay $Q4 (D_j I_j)$ (Longest Delay)	-0.219*** (0.012)	-5.027*** (0.146)	-2.848*** (0.119)	-2.410*** (0.108)	-0.618*** (0.049)	-0.243*** (0.029)	-0.578*** (0.053)	-0.414*** (0.037)
Intensity Q2								
Delay Q1 $(D_1 I_2)$		l		I	l	l	1	I
Delay Q2 $(D_j I_j)$	-0.034* (0.013)	-1.228*** (0.156)	-0.876*** (0.127)	-1.007*** (0.115)	-0.211*** (0.052)	-0.156*** (0.031)	-0.218*** (0.056)	-0.194*** (0.039)
Delay Q3 (D_3I_2)	-0.096*** (0.013)	-2.573*** (0.157)	-1.592*** (0.128)	-1.617*** (0.116)	-0.407*** (0.052)	-0.181*** (0.031)	-0.312*** (0.057)	-0.331*** (0.040)
Delay Q4 $(D_j I_j)$	-0.145*** (0.014)	-3.789*** (0.160)	-2.191*** (0.130)	-2.014*** (0.118)	-0.551*** (0.053)	-0.197*** (0.032)	-0.473*** (0.058)	-0.390*** (0.040)

APPENDIX A (continued)
Academic Outcomes, by Search Delay and Intensity

						IGETC	IGETC Subcategories	
	Took a Course	Total Units	Associate Degree Units	IGETC Units	Math	Humanities	Social Science	Biological Science
Intensity Q3								
Delay Q1 $(D_j I_3)$	0.043***	0.936*** (0.152)	0.634***	0.486***	0.150** (0.051)	0.045 (0.030)	0.143** (0.055)	0.020 (0.038)
Delay Q2 (D_2I_3)	-0.008 (0.013)	-0.323* (0.155)	-0.182 (0.126)	-0.476*** (0.115)	0.001 (0.052)	-0.059 (0.031)	-0.074 (0.056)	-0.179*** (0.039)
Delay Q3 (D_3I_3)	-0.026 (0.013)	-0.946*** (0.158)	-0.564*** (0.128)	-0.913*** (0.117)	-0.168** (0.053)	-0.105*** (0.031)	-0.049 (0.057)	-0.240*** (0.040)
Delay Q4 $(D_{\downarrow}I_3)$	-0.068*** (0.014)	-2.125*** (0.162)	-1.503*** (0.132)	-1.529*** (0.120)	-0.432*** (0.054)	-0.154*** (0.032)	-0.248*** (0.059)	-0.334*** (0.041)
Intensity Q4 (Most Intense Search)					,			
Delay Q1 $(D_j I_j)$	0.056***	1.722*** (0.150)	1.477*** (0.122)	1.167*** (0.111)	0.420***	0.033	0.201*** (0.054)	0.223*** (0.038)
Delay Q2 (D_2I_4)	0.037** (0.013)	1.223*** (0.156)	0.974*** (0.127)	0.548*** (0.115)	0.305***	-0.023 (0.031)	0.239***	-0.077 (0.039)
Delay Q3 (D_3I_4)	0.016 (0.014)	0.365* (0.159)	0.289* (0.129)	-0.142 (0.117)	0.211***	-0.032 (0.031)	0.073 (0.057)	-0.168*** (0.040)
Delay Q4 $(D_{\downarrow}I_{\downarrow})$	-0.009 (0.014)	-0.604*** (0.162)	-0.340** (0.132)	-0.725*** (0.120)	-0.172** (0.054)	-0.101** (0.032)	-0.037 (0.059)	-0.274*** (0.041)
Intercept	0.936*** (0.011)	9.626*** (0.127)	4.574*** (0.094)	5.429*** (0.103)	1.009***	0.455***	1.043***	0.554***
N	22,851	22,851	22,851	22,851	22,851	22,851	22,851	22,851

Notes. All regressions include registration appointment fixed-effects and demographic (age, sex, ethnicity) controls. The reference category are students classified as $D_j I_j$ (i.e., the lowest delay quartile and in the second lowest intensity quartile).

****p < 0.001. ***p < 0.001. **p < 0.001. **p < 0.05.

APPENDIX B

Total Units Attempted, by Registration Group

	Cor	Continuing	Second	Second Semester		New
Intensity Quartile 1 (Least Intense Search)						
Delay Quartile 1 (D, I_j) (Shortest Delay)	-3.401***	-1.859***	-2.260***	-1.249**	-1.939***	-1.526***
	(0.209)	(0.186)	(0.437)	(0.397)	(0.413)	(0.372)
Delay Q2 $(D_j I_i)$	-4.864***	-2.869***	-3.918***	-2.779***	-2.203***	-1.879***
	(0.190)	(0.172)	(0.402)	(0.369)	(0.401)	(0.362)
Delay Q3 $(D_j I_i)$	-5.598***	-3.336***	-4.307***	-3.082***	-3.002***	-2.230***
	(0.182)	(0.166)	(0.392)	(0.359)	(0.409)	(0.368)
Delay Q4 $(D_i I_i)$ (Longest Delay)	-6.473*** (0.175)	-3.977*** (0.162)	-4.732*** (0.374)	-3.598*** (0.346)	-2.813*** (0.402)	-2.525*** (0.361)
Intensity Q2						
Delay Q1 $(D_i I_2)$	l	l	1			
Delay Q2 (D_2I_2)	-1.570***	-1.010***	-0.856*	-0.826*	-1.105*	-1.112**
	(0.186)	(0.164)	(0.425)	(0.385)	(0.442)	(0.397)
Delay Q3 (D_jI_j)	-2.988***	-1.901***	-2.399***	-2.026***	-1.710***	-1.540***
	(0.189)	(0.169)	(0.410)	(0.372)	(0.442)	(0.399)
Delay Q4 $(D_iI_{\hat{i}})$	-4.685***	-3.150***	-2.942***	-2.459***	-1.633***	-1.423***
	(0.192)	(0.174)	(0.422)	(0.385)	(0.441)	(0.397)

APPENDIX B (continued)

Total Units Attempted, by Registration Group

	Cor	Continuing	Second	Second Semester		New
Intensity Q3						
Delay QI (D_lI_j)	0.930*** (0.183)	0.427**	1.529*** (0.407)	0.956** (0.369)	1.286** (0.423)	1.172** (0.380)
Delay Q2 $(D_2 I_3)$	-0.495** (0.186)	-0.418* (0.165)	0.420 (0.415)	0.045 (0.375)	-0.172 (0.448)	-0.347 (0.402)
Delay Q3 $(D_{i}I_{j})$	-1.145*** (0.189)	-0.978*** (0.168)	-0.234 (0.429)	-0.536 (0.391)	0.500 (0.435)	0.009 (0.392)
Delay Q4 $(D_{_J}I_{_J})$	-2.726*** (0.196)	-1.835*** (0.176)	-0.869* (0.430)	-1.028** (0.392)	0.062 (0.434)	-0.3 <i>57</i> (0.391)
Intensity Q4 (Most Intense Search)						
Delay Q1 $(D_l I_l)$	1.726*** (0.181)	0.898*** (0.161)	2.456*** (0.397)	1.268*** (0.363)	2.595*** (0.410)	2.065*** (0.368)
Delay Q2 (D_2I_4)	1.079*** (0.189)	0.437** (0.169)	2.694*** (0.403)	1.493*** (0.369)	2.270*** (0.422)	1.904*** (0.379)
Delay Q3 $(D_{\beta}I_{\gamma})$	0.094 (0.191)	-0.215 (0.171)	1.319** (0.417)	0.781*	2.234*** (0.433)	1.569*** (0.392)
Delay Q4 $(D_j I_j)$	-0.943*** (0.195)	-0.740*** (0.175)	0.427 (0.439)	0.250 (0.404)	1.611***	1.111**
Student Controls ^a	Z	>	Z	X	Z	Y
Intercept	9.090*** (0.132)	8.078*** (0.163)	7.859*** (0.288)	9.101*** (0.422)	4.994*** (0.311)	6.685***
N	16,268	16,057	3,751	3,682	3,112	3,039

Note. All regressions include registration appointment fixed-effects. The reference category are students classified as D_L_2 (i.e., the lowest delay quartile and in the second lowest intensity quartile).

*Student controls includes demographics (age, gender, and ethnicity), academics (math and English levels, cumulative GPA, units taken the previous semester), and behavioral (previous delay and intensity measures). New students do not have academic or behavioral controls.

***p < 0.001. **p < 0.01. *p < 0.05.

APPENDIX C IGETC Units Attempted, by Registration Group	ìroup					
	Cor	Continuing	Second	Second Semester		New
Intensity Quartile 1 (Least Intense Search)						
Delay Quartile 1 $(D_i I_i)$ (Shortest Delay)	-2.204*** (0.160)	-1.139*** (0.146)	-1.065*** (0.301)	-0.603* (0.282)	-0.511 (0.276)	-0.635 (0.333)
Delay Q2 (D_2I_j)	-3.004*** (0.146)	-1.506*** (0.135)	-1.690*** (0.276)	-1.248*** (0.262)	-0.951*** (0.268)	-0.811* (0.323)
Delay Q3 (D_3I_i)	-3.392*** (0.139)	-1.632*** (0.130)	-1.717*** (0.270)	-1.248*** (0.255)	-1.109*** (0.273)	-1.227*** (0.330)
Delay Q4 $(D_i I_i)$ (Longest Delay)	-3.563*** (0.134)	-1.718*** (0.127)	-2.070*** (0.257)	-1.518*** (0.246)	-1.153*** (0.268)	-1.348*** (0.324)
Intensity Q2 Delay Q1 $(D_i I_j)$	I	I		I		I
Delay Q2 (D_2I_2)	-1.416*** (0.142)	-0.891*** (0.129)	-0.586* (0.292)	-0.714** (0.273)	-0.338 (0.296)	-0.488 (0.357)
Delay Q3 (D_3I_2)	-2.106*** (0.145)	-1.152*** (0.133)	-1.148*** (0.282)	-1.140*** (0.264)	-0.543 (0.295)	-0.775* (0.357)
Delay Q4 $(D_{\downarrow}I_{\downarrow})$	-2.892*** (0.147)	-1.637*** (0.136)	-0.990*** (0.290)	-0.846** (0.273)	-0.415 (0.294)	-0.553 (0.356)

APPENDIX C (continued)
IGETC Units Attempted, by Registration Group

	Cor	Continuing	Second	Second Semester		New
Intensity Q3						
Delay QI (D_jI_3)	0.608***	0.333** (0.126)	0.779**	0.284 (0.262)	0.438 (0.282)	0.615 (0.341)
Delay Q2 (D_2I_3)	-0.686*** (0.142)	-0.400** (0.129)	0.024 (0.285)	-0.274 (0.266)	0.192 (0.299)	0.256 (0.361)
Delay Q3 (D_jI_j)	-1.224*** (0.145)	-0.876*** (0.132)	0.079 (0.295)	-0.148 (0.278)	0.222 (0.291)	0.361 (0.351)
Delay Q4 $(D_{i}I_{j})$	-2.158*** (0.150)	-1.358*** (0.138)	-0.508 (0.296)	-0.555* (0.279)	0.491 (0.290)	0.566 (0.350)
Intensity Q4 (Most Intense Search)						
Delay Q1 (D_II_{\downarrow})	1.362*** (0.138)	0.702*** (0.126)	1.714*** (0.273)	0.844** (0.258)	1.019*** (0.274)	1.819*** (0.331)
Delay Q2 (D_2I_{\downarrow})	0.529*** (0.145)	0.218 (0.133)	1.321*** (0.277)	0.576* (0.262)	1.265*** (0.282)	1.822*** (0.340)
Delay Q3 (D_3I_{ϕ})	-0.329* (0.147)	-0.340* (0.134)	0.619*	0.241 (0.271)	0.960*** (0.289)	1.363*** (0.350)
Delay Q4 $(D_{\mu}I_{\mu})$	-1.096*** (0.149)	-0.670*** (0.137)	0.375 (0.302)	0.274 (0.287)	0.657*	1.213*** (0.346)
Student Controls ^a	Z	>	Z	¥	Z	X
Intercept	4.090*** (0.101)	5.087*** (0.128)	2.512*** (0.198)	5.634*** (0.300)	1.595*** (0.208)	2.338*** (0.251)
N	16,268	16,057	3,751	3,682	3,112	3,039

Note. All regressions include registration appointment fixed-effects. The reference category are students classified as $D_I _2$ (i.e., the lowest delay quartile and in the second lowest intensity quartile).

*Student controls includes demographics (age, gender, and ethnicity), academics (math and English levels, cumulative GPA, units taken the previous semester), and behavioral (previous delay and intensity measures). New students do not have academic or behavioral controls.

****p < 0.001.*** p < 0.001.** p < 0.05.